Research of Influence Diffusion Based on Multi-agent Theory in Social Networks

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Abstract—**Studies on information dissemination and influence diffusion in social networks have received extensive attention from researchers, but most look at information diffusion from a global perspective. Since most studies did not describe personalization in detail, in this paper, combined with social networks analysis and multi-agent modeling method, a new distributed modeling method for influence diffusion in directional networks is proposed. In the given model, a wealth of individual psychological factors are added to describe personalized characteristics. The simulation results show that the model is more suitable for simulating the diffusion of influence in the real world, providing a reference method for exploring the relationship between individuals and complex social phenomena.**

Keywords-Multi-agent; agent-based modelling; influence diffusion; complex network

I. INTRODUCTION

Influence spreading modeling is the core work of influence spreading analysis. Nowadays, most influence spreading modeling is a simple centralized spreading process [1]. Existing traditional influence diffusion models such as Independent Cascade Model (ICM) and Linear Threshold Model (LTM) are often used to describe the influence diffusion process. However, these two models still have some limitations. It is mainly reflected in the fact that influence dissemination individuals and the dissemination process are considered homogeneous, making it difficult to express complex individual characteristics and individual differences. When analyzing the influence of social networks, the traditional centralized model will be difficult to apply if each individual's unique personalization parameters are considered. Multi-agent computing has been conceived as a powerful paradigm for modeling the interaction of multi-agent systems [2]. Agents are positive and can influence each other, and can show the actual situation of individual interactions. In addition, the multi-agent model focuses on describing the microscopic performance of individuals and can explore how changes in low-level parameters impact the behavior at a whole-system level [3] and is more suitable for using micro individuals to study the macro world [4]. Integrating agent-based modeling and social networks analysis can deeply understand human behavior [5].

To explore social phenomena, a lot of research work focused on agent-based modeling. Li et al. considered the user's personalized characteristics and preference status to model different influence propagation processes [6]. Van Maanen et al. obtained network structure and personal behavior parameters from empirical data and studied the influence spread of social networks through various behavior patterns [7]. Li and Bai et al. proposed an agent-based influence maintenance model to learn how to maintain long-term influence in social networks [8]. Eunice E. Santos et al. introduced a Culturally Infused Agent Based Modeling (CI-ABM) Framework and proposed a computational model for disseminating medical guidelines[9]. ABM has shown many advantages in modeling and simulating the micro-individual level in complex systems [10] [11].

In this paper, a multi-agent-based model of influence propagation (MABIPM) is proposed, which describes the influence propagation process by focusing on micro-individual interactions. The model is applied to the existing Wiki Vote network. In different simulation scenarios, the model can capture the expected state and long-term evolution trend of the network. Finally, after applying a positive marketing strategy, the number of individuals in the positive acceptance state in the network has increased significantly, which is in line with reality and proves the rationality and effectiveness of the MABIPM model.

The organization structure of this paper is as follows: in the second section, some related work is introduced; in the third section, the multi-agent based influence propagation model is presented in detail; in the fourth section, simulation and analysis are carried out, and finally, the paper is summarized in the fifth section.

II. RELATED WORK

The main agent-based modeling idea is used in the research of references [6]-[11], and the influence diffusion process is described through different modeling methods. In agent-based modeling, the meaning of agent and environment are two key factors that cannot be ignored. The agent and environment in this paper should be declared separately:

A. Agent and Social Environment

1) An agent represents users who have autonomy in the social environment and can interact with the environment. Mathematically, Agent is defined as a vertex v_i, $v_i \in V$ on a directed weighted complex network $G = (V, E)$, where $V = \{v_1, \ldots, v_n\}$ represents the set of agents, $E = \{e_{ij} | 1 \leq i, j \leq$

$n\}$, $i, j \in \mathbb{N}$. The weight of edge e_{ij} represents the influence propagation strength from v_i to v_j. The neighbors of agent v_i is $N(v_i)$,if v_j is the neighbor of v_i ,then $\{e_{ij}\} \cup \{e_{ji}\} \subseteq E, v_j \in N(v_i)$.

2) In a multi-agent system, the environment is another critical factor. The agent perceives the environment through sensors, produces a series of autonomous behaviors after interacting with the environment, and finally feeds back through effectors. Usually, each agent only pays attention to the resources that are accessible in the local environment. In our model, each agent regards all reachable neighbors as the main factor of the social environment and uses this to perceive the global social environment.

There are a variety of modeling methods when describing the individual characteristics of an agent, and psychological factors are one of them. In applying psychology to information diffusion, Weng et al. borrowed cognitive mechanisms and behavioral models to model information diffusion in social networks [12]. Rao and Georgeff use the mental model belief-desire-intention (BDI) in the agent's computational decision [13]. Inspired by the above studies, some psychological concepts are used in this model.

B. *Introduction to Psychological Concepts*

1) **Psychological distance**. Psychological distance refers to subjective judgments based on the distance between an object and a reference point [14].

2) **Cognitive resources**. Cognitive resources refer to the energy people need in cognitive processing activities, which are used to control attention and regulate emotions, etc. [15].

3) **Stereotype**. Stereotype refers to prejudice about something, which is often strong and hinders our understanding of unknown objects [16].

In this paper, our modeling method considers the agent's individual characteristics and social, environmental influence factors, and the activation of influence among individuals depends on these two parts. In addition, to describe the specific attitudes of different individuals towards the same thing, we set the acceptance state for agents and consider updating it at each moment. Based on the above factors, we propose a multi-agent system for influence propagation (IPMAS), which models users as agents and propagation process as a constantly updated behavioral process in social networks.

III. INFLUENCE PROPAGATION MULTI-AGENT SYSTEM

Individuals or entities are regarded as autonomous agents. They are in the same environment, can communicate with their immediate neighbors, and are affected by the environment. This is the main idea based on agent-based modeling. In IPMAS, each agent has multiple psychological attributes and behavioral rules (defined in detail below). The agent's acceptance status depends on the individual's internal impression of the propagation item and comprehensive social influence. Therefore, in the proposed system framework, an agent considers internal perceptions and external environmental factors to make decisions and adjust the acceptance state. In each time step, the agent spreads its influence through interaction with neighbors. In the end, agents in the network interact and try to achieve a stable convergence state.

From a micro perspective, each agent considers the local environment centered on itself, and the agent uses the acceptance status of its neighbors to obtain comprehensive social influence. When the agent is affected by neighbors with the same or opposite attitudes, it will increase the possibility of maintaining or modifying the current state. From a macro perspective, IPMAS shows the emergence of groups driven by individual behavior. The entire network reflects the evolution of the overall user trend in social networks according to the decentralized behavior of each agent.

In summary, the behavior framework of a single agent in Figure 1 is proposed. Agents use the topological structure of complex networks to build a local influence-spreading environment. Then agents judge whether to update the state according to its psychological factors. If they update the state, they will update the acceptance state by combining its inner impression and the comprehensive social influence. The following subsections introduce the agent's attribute definition and behavior rules in detail.

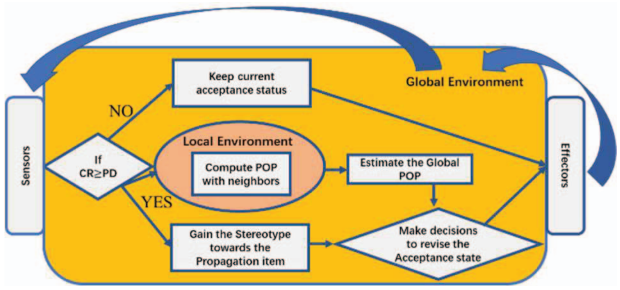

Figure 1. The behavioral framework of a single agent.

A. *Agent's Acceptance Status*

Each agent has three acceptance states for a specific item after being activated, namely, Positively Accepted, Negatively Accepted, and Indifferent. At each time step t, the agent's acceptance state is S_i^t, $S_i^t \in \{PA, IA, NA\}$.Among them, S_i^t=PA means that the agent v_i has a positive acceptance attitude towards the specific item and will transmit a positive influence to its neighbors $N(v_i)$, persuading neighbors to have the same positive acceptance attitude. On the contrary, S_i^t=NA, it means that the agent v_i has a negative attitude towards a specific item and will pass a negative influence to neighbors. For S_i^t=IA, it will maintain a neutral and indifferent attitude towards a specific item.

B. *Agent Attribute Definition*

1) **Agent's psychological distance and cognitive resources**. The psychological distance can be explained from different perspectives. In general, PD_i in this paper refers to the degree of familiarity of the agent v_i with the spread of information. Cognitive resources are the energy needed to

obtain information. People must have psychological resources to successfully complete various cognitive tasks. Therefore, in this paper, we stipulate that only the agent v_i will consider revising his acceptance status when the cognitive resource CR_i exceeds the psychological distance PD_i. The state revision judgment formula is as (1).

$$revise_i = \begin{cases} 0, & CR_i < PD_i \\ 1, & CR_i \geq PD_i \end{cases} \quad (1)$$

2) **Agent's stereotypes and public opinion pressure**. Stereotype ste_i refers to the specific view of the agent v_i on the propagation item based on past experience. There is not much research on stereotype modeling. In this paper, the ste_i is quantified as a value between [0,1], it is stipulated that the closer its value is to 0, the more negative view of v_i on the history of the propagation item is. On the contrary, the closer to 1, the more positive view of the history of the propagation item is.

In addition, a simple threshold model and individual's stereotypes are used to obtain the initial acceptance state of the individual v_i for the propagation item, that is S_i^0. Given two predefined thresholds θ_{PA} and threshold θ_{NA} to represent the PA threshold and NA threshold, respectively, there is the following formula (2).

$$S_i^0 = \begin{cases} PA, & if\ ste_i > \theta_{PA} \\ NA, & if\ ste_i < \theta_{NA} \\ IA, & Otherwise \end{cases} \quad (2)$$

3) **Public opinion pressure.** The public opinion pressure comes from the public opinion pressure exerted by the surrounding environment on the agent v_i. The pop_i^s is defined as social public opinion pressure exerted on the agent v_i by neighbors in the state of S, requiring that its acceptance state be modified or retained as S, where $S \in \{PA, IA, NA\}$. The more neighbors that have different acceptance states from its own, the more likely it is that v_i will modify opinion. The calculation method of the public opinion pressure of the agent v_i are as formulas (3) and (4).

$$pop_i^s = \exp\left(\sum_{v_j \in N(v_i),\ s_j = S} strength_{ji}\right) \quad (3)$$

$$strength_{ji} = \frac{|N(v_j) \cap N(v_i)|}{\min\{k_j, k_i\}} \quad (4)$$

where $strength_{ji}$ represents the influence propagation strength between the agent v_i and the agent v_j, and the natural index represents the external environmental public opinion pressure that the agent v_i receives, amplified by the pressure of neighbors. Since agents have a perception of the global environment, it is assumed even when the total intensity of the neighbor's influence is 0, there will be a small amount of social public opinion pressure imposed by the external environment, and the minimum is 1. S represents the acceptance status of the agent v_i to the propagation item. where k_j and k_i respectively represent the number of neighbors of the two agents and the fractional numerator is the number of neighbors in common between the two agents.

C. Probability of Revising Acceptance State

$prs_i(s_i'|s_i)$ represents the probability that the agent v_i will change from the current acceptance state s_i to another state s_i'. Three factors need to be considered. First, judge whether the agent v_i is revised according to formula (1). If a revision is considered, ie $revise_i$=1, then comprehensively consider how the agent v_i will revise the current acceptance status based on the stereotypes ste_i and the public opinion pressure pop_i. The specific formulas are shown in (5), (6), and (7).

$$prs_i(PA|s_i) = \begin{cases} \lambda_i \cdot ste_i + (1-\lambda_i) \cdot \frac{pop_i^{PA}}{\sum_{S \in \{PA,IA,NA\}} sop_i^s}, & revise = 1 \\ 1, & revise = 0,\ s_i^t = PA \\ 0, & \text{others} \end{cases} \quad (5)$$

$$prs_i(NA|s_i) = \begin{cases} \lambda_i \cdot (1 - ste_i) + (1-\lambda_i) \cdot \frac{pop_i^{NA}}{\sum_{S \in \{PA,IA,NA\}} sop_i^s}, & revise = 1 \\ 1, & revise = 0,\ s_i^t = NA \\ 0, & \text{others} \end{cases} \quad (6)$$

$$prs_i(IA|s_i) = \begin{cases} (1-\lambda_i) \cdot \frac{pop_i^{IA}}{\sum_{S \in \{PA,IA,NA\}} sop_i^s}, & revise = 1 \\ 1, & revise = 0, s_i^t = IA \\ 0, & \text{others} \end{cases} \quad (7)$$

where $prs_i(PA|s_i)$ and $prs_i(NA|s_i)$ respectively represent the probability that the agent v_i will modify the propagation item from any acceptance state to PA and NA, where λ_i stands for v_i the degree of stubbornness and is also a trade-off between the stereotypes and the public opinion pressure. $prs_i(IA|s_i)$ only considers the weighted public opinion pressure factor. This is because if agents change from any state to a state of indifference, it means that the previous stereotypes has been discarded. At any time, there is $prs_i(PA|s_i) + prs_i(NA|s_i) + prs_i(IA|s_i) = 1$.

D. State Transition Probability Characteristics

In the initial stage of the network, a three-dimensional diagram of the state transition probability of user No. 10 with the number of positive neighbors (NoPN) and stereotypes is obtained. As shown in Figure 2, $prs_{10}(PA|s_{10})$ will increase with the number of positive neighbors and stereotypes. This is because the more positive the user's view of the propagation item and the greater the pressure of positive social public opinion provided by neighbors, the greater the probability that the user will revise the acceptance status to be positive. Obviously, the probability of revision to the negative state and the neutral state at this time is smaller.

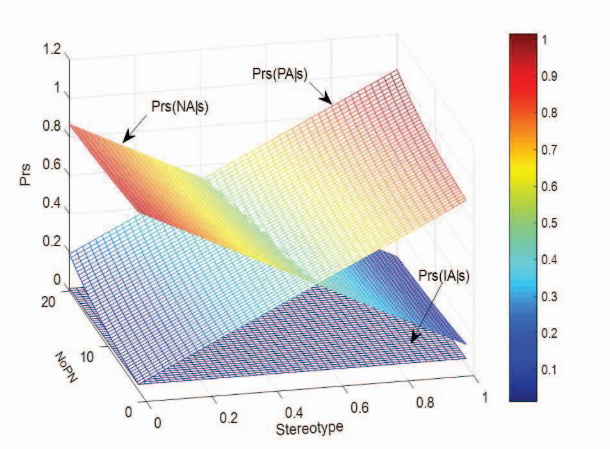

Figure 2. Three-dimensional diagram of state transition probability.

IV. SIMULATION AND ANALYSIS

In this section, two sets of simulations are conducted. The first set of simulations aims to track, predict, and analyze the evolution of social networks' influence diffusion without interference by using MABIPM. The second set of simulations uses a positive marketing strategy, ie, sowing positive state seeds before the beginning of the network evolution and observing the changes in the number of people who positively accept a propagation item before and after the sowing. The data set used in the simulation is Wiki Vote. This network contains all Wikipedia voting data from the creation of Wikipedia to January 2008. There are 7,115 nodes and 103,689 edges in total. The nodes in the network represent wiki users, numbered from 1 to 7115, and the directional edge is the voting relationship sent by user i to user j.

A. The Initial Settings of the Simulation

Before the network starts to evolve, by generating [0,1] uniformly distributed random numbers, users' stereotypes, psychological distance, and stubbornness are obtained. The psychological distance does not change much in a short time, but the cognitive resources will fluctuate greatly. Therefore, the cognitive resources of all users have randomly changed values at each time step t, in the range [0,1] between.

B. Network Evolution Simulation

The first set of simulations set two simulation scenarios. To observe the evolution process completely, we set the fixed step length of the network evolution as 100. First, assume that the stereotypes of the entire network users on the propagation item obey a uniform distribution. In addition, in formula (2), let θ_{PA}=0.8 and θ_{NA}=0.2 obtain the initial state distribution of the network. In Figure 3, it can be observed that the initial state of the network accounts for more users who are indifferent and less for positive and passive users. With the evolution of the network, the PA node and the NA node began to rise simultaneously, and the IA node dropped rapidly. After about 15-time steps, the three states basically reached global stability, with only some slight fluctuations, and eventually, the number of negatives accounted for more. It can be concluded that with the uniform distribution of stereotypes, the negative influence of the network ultimately dominates. Then, adjust the distribution of user stereotypes, 80% of users are greater than 0.5, and 20% of users are less than 0.5, which means that the proportion of people with better stereotypes has increased significantly, and adjust θ_{PA}=0.88, θ_{NA}=0.5 to get the same initial state distribution of the network. As can be seen in Figure 4, neutral resources are quickly preempted. About 15-time steps, the network tends to stabilize, the positive impact becomes very obvious, dominates, and the negative impact is relatively more minor. Figure 5 shows the running results under 80% of the poor stereotypes, and it is found to be the opposite of the developments in Figure 4. This indicates that the public's accurate impression and prior evaluation have played a vital role in the spread of influence.

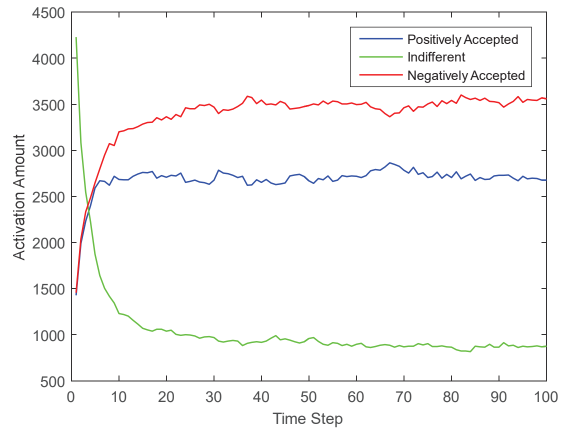

Figure 3. Network evolution trend under the uniform distribution of stereotypes.

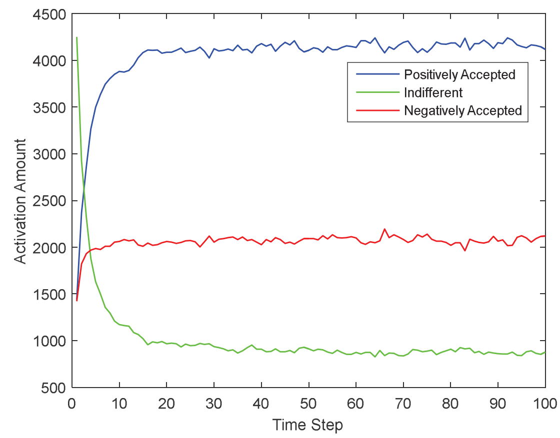

Figure 4. 80% better stereotypes account for the network evolution trend.

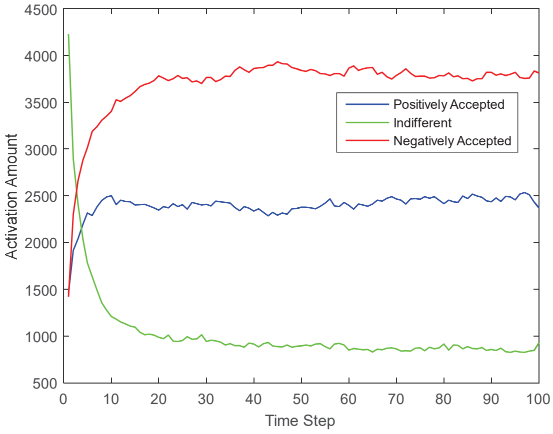

Figure 5. 80% worse stereotypes account for the network evolution trend.

C. *Network Evolution Simulation After Adding Positive Marketing Strategy*

In some practical application scenarios, such as product marketing, to promote products or spread information, it is often necessary to invest specific resources in fixed-point publicity and select influential users to spread the influence of the product. In the following settings, it is assumed that the seed node can be selected from users in any state, and the seed node is locked into a positive acceptance state and will not be changed during the network evolution for product marketing. In Figure 3, the network ultimately has more users with a negative attitude than a positive attitude, which is not conducive to product marketing, so the top 100 nodes with the largest out-degree in the network are selected as seed nodes. As shown in Figure 6, after joining the positive marketing strategy, the number of users with a positive attitude of acceptance in the network eventually increased. The number of users with a negative attitude of acceptance decreased. The number of positive users surpassed the number of negative users, which shows that our positive marketing strategy has produced good results. And this paper also tested the number of final positive users of the network under different seed sets. As shown in Figure 7, it can be found that as the number of seed sets increases, the number of active users in the final network will gradually increase.

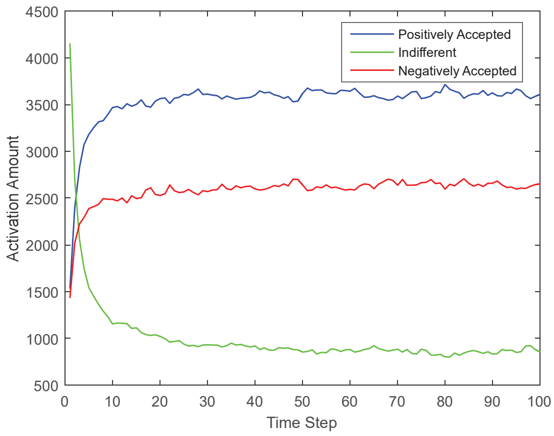

Figure 6. Network evolution trend after joining positive marketing strategy.

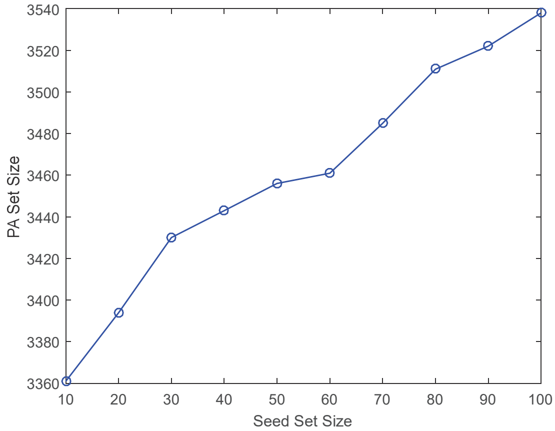

Figure 7. The number of active users in the network under different seed sets.

D. *Discussion*

In summary, in the first set of simulations, it can be found that MABIPM can be used to track the evolution of the network in different simulation scenarios. In the second set of simulations, positive marketing strategies can make the network as a whole move in a more positive direction. The development fits the reality well, that is, our proposed MABIPM can predict and analyze influence spread and network evolution.

V. CONCLUSION

In this paper, we have used the concept of the multi-agent system to model the influence spread on the social network and proposed a distributed influence spread model MABIPM to track and predict the development trend of network influence. Compared with the global network topology, this paper paid more attention to personalized parameters, psychological factors, and behavioral decisions. The information dissemination in social networks is modeled as an evolutionary process driven by individual behavior. The simulation showed that the proposed model is suitable for dynamic environments and complex networks. In the network evolution under different circumstances, it can be found that the model could track the long-term evolution trend of social networks driven by influence forces and can fit the reality very well. This model reveals the relationship between individuals and social phenomena from scientific calculations and provides a reference method for media information dissemination management and government policymaking. In the future, we plan to apply it to some practical problems to prove the model's feasibility further.

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